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Multilevel Regression Analyses to Investigate the Relationship Between Two Variables Over Time: Examining the Longitudinal Association Between Intrusion and Avoidance

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Multilevel modeling is a powerful and flexible framework for analyzing nested data structures (e.g., repeated measures or longitudinal designs). The authors illustrate a series of multilevel regression procedures that can be used to elucidate the nature of the relationship between two variables across time. The goal is to help trauma researchers become more aware of the utility of multilevel modeling as a tool for increasing the field's understanding of posttraumatic adaptation. These procedures are demonstrated by examining the relationship between two posttraumatic symptoms, intrusion and avoidance, across five assessment points in a sample of rape and robbery survivors (n = 286). Results revealed that changes in intrusion were highly correlated with changes in avoidance over the 18-month posttrauma period.

As theories accounting for adaptation following exposure to traumatic events become more sophisticated, they increasingly include predictions about the course of adaptation over time (e.g., Bonnano, 2004). In addition, research examining risk and resiliency factors has demonstrated that adaptation following trauma involves a complex interplay of multiple factors (see Vogt, King, & King, 2007). Enhancing our understanding of posttraumatic adaptation requires testing complex hypotheses involving the relationships among multiple variables across time (Litz, 2007). Fortunately, recent advances in quantitative methodologies allow trauma researchers to respond to the call for improved multivariate, longitudinal, and prospective research. The purpose of this article is to demonstrate how multilevel regression analyses can be used to investigate the relationship between two variables across multiple assessment occasions. For example, trauma researchers might want to understand the association between substance use and symptoms of posttraumatic stress disorder (PTSD) when both have been measured on multiple occasions (e.g., Coffey, Schumacher, Brady, & Cotton, 2007), or they might be interested in evaluating whether changes in PTSD over time are related to changes in life satisfaction (e.g., Schnurr, Hayes, Lunney, McFall, & Uddo, 2006).

Three multilevel regression techniques are demonstrated. First, we show how to examine the bivariate association between two variables across multiple time points. Second, we describe standard (univariate) growth curve analyses to depict the nature of change over time separately for two variables. Finally, we illustrate a multivariate change procedure described by MacCallum, Kim, Malarkey, and Kiecolt-Glaser (1997) to elucidate how change over time in one variable is related to change over time in another variable (i.e., correlation of change). Although our main goal here is to explicate multilevel analytic techniques, in doing so we investigate a relationship that is of interest for trauma researchers (e.g., Creamer, Burgess, & Pattison, 1992): the relationship between posttraumatic symptom clusters of intrusion (or reexperiencing) and avoidance. We demonstrate the use of these techniques using data from 340 rape or robbery survivors (described below).

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ASSESSING THE STRENGTH AND NATURE OF A BIVARIATE RELATIONSHIP ACROSS TIME

Multilevel regression techniques were developed to analyze nested or hierarchical data structures (e.g., Raudenbush & Bryk, 2002). For a longitudinal design, repeated assessments are nested within individuals. The repeated-measures, or within-subjects, component of the model is referred to as Level 1, whereas the between-individuals component of the model is referred to as Level 2. For our demonstration, repeated assessments of intrusion and avoidance symptomatology make up Level 1, which are nested within individuals, the Level 2 component of the model. Understanding the regression equations is essential to understanding multilevel models.

The equation often used to describe standard (cross-sectional) linear regression analyses is as follows:

$$Y = b_0 + b_1 X + e^1 \tag{1}$$

The outcome variable Y is described as a function of a predictor variable X, an intercept term b_0, and a residual term e. The regression coefficient associated with predictor b_1, or the slope term, provides an estimate of the strength of the association between the predictor and outcome (i.e., an increase of one unit in the predictor variable is associated with b_1 unit increase in the outcome), the estimate of the intercept b_0 indicates the predicted value of Y when the predictor X is zero, and the residual e indicates the distance between the predicted value of Y and the actual observed value of the outcome variable (i.e., unexplained, leftover, or error variance). This standard regression equation needs to be adapted for nested or hierarchical data to account for (a) the fact that each individual (Level 1 unit) has multiple data points, and (b) there are multiple sources of error-Level 1, or within-subjects, and Level 2, or between subjects. The Level 1 regression equation for assessing the bivariate relationship across multiple occasions is

$$Y_{it} = b_{i0} + b_{i1} X_{it} + e_{it} \tag{2}$$

As in standard regression, Y denotes the outcome variable. Because each individual has multiple data points, the subscripts i and t signify that the regression equation is predicting a particular score on this outcome variable for an individual participant i, at a specific point in time, t. Next, b_{i0} denotes the intercept for participant i, and b_{i1} denotes the slope coefficient for the regression of the outcome variable Y on the predictor variable X for participant i. Finally, e_{it} represents the Level 1 regression residual term (i.e., unexplained, leftover, or error variance) indicating how far a data point deviates from the expected value (or regression line) for participant i. It helps to think of the Level 1 component of a multilevel analysis as fitting separate regression lines for each participant producing estimates of the intercept (b_{i0}) and slope (b_{i1}) for all Level 2 units (i.e., participants).

The purpose of the Level 2 component of the model is to evaluate how the Level 1 coefficients are distributed, both in terms of mean level and variability, across Level 2 units (i.e., participants). Therefore, there is always one Level 2 regression equation for each Level 1 regression coefficient:

$$b_{i0} = G_{00} + U_{i0} \tag{3}$$

$$b_{i1} = G_{10} + U_{i1} \tag{4}$$

These equations provide two types of estimates. Estimates referred to as *fixed effects* (G_{00} and G_{10}), depict the mean of the Level 1 coefficients across Level 2 units (i.e., participants), whereas the *random effects* or variance component of the model (U_{i0} and U_{i1}) describe how much dispersion or variability there is in Level 1 coefficients across Level 2 units. Let us now look at the Level 2 equations more closely. The dependent variables for these equations are the Level 1 regression coefficients. For the equation predicting initial status (b_{i0}), G_{00} represents initial status aggregated across all participants, and U_{i0} is the Level 2 regression residual indicating the difference between that particular individual's initial status and the overall/aggregated initial status. Likewise, for the equation predicting slope (b_{i1}), G_{10} represents the strength and direction of this association aggregated, or averaged, across all participants and provides an estimate of the bivariate association between the predictor and outcome variable. U_{i1} is the Level 2 regression residual indicating the difference between that particular individual's slope and the average slope of the sample.

The variance component of multilevel models includes estimates of the total Level1 (within-subjects) variability, or variance, which is often referred to as σ^2 and is derived from each individual's estimate of e_{it}, as well as Level 2 (across participants) variability, or individual differences, in the intercept and slope, which are derived from each individuals estimates of U_{i0} and U_{i1}, respectively. In addition, the variance component of multilevel models includes estimates of the covariance among random effects. However, this is more germane to models discussed later when we examine the associations between initial status and change over time and associations between two growth parameters in growth curve models and will be described later. In sum, multilevel models produce estimates of mean level and variance (i.e., individual differences in the Level 1 coefficients across Level 2 units) in the parameters.

Several clarifications about this initial model are warranted. First, the intercept terms b_{i0} and G_{00} can be interpreted as the value of the outcome Y_{it}, when the predictor variable is zero. In some instances, such as when a score of zero is not possible or meaningful (e.g., an individual cannot have zero or no weight), the predictor variable can be mean centered. Mean centering consists of subtracting the mean value of a variable from each score in

[1]We adopted a revised version of the notational system used by Raudenbush and Bryk (2002).

a distribution so that the intercept coefficient can be interpreted as the value of the outcome at the mean of the predictor variable (instead of the value of the outcome when the predictor variable is zero in the raw score metric, as is the case for noncentered predictors; see Enders and Tofighi, 2007, for a discussion of centering in a multilevel regression framework). The second clarification regards the interpretation of b_{i1} and G_{10}. These slope terms represent the bivariate association between the predictor and outcome (i.e., are higher/lower levels of the predictor variable associated with higher/lower levels of the outcome?) when taking into account the nested, or hierarchical, structure of the data. Although in the longitudinal framework the predictor and outcome variables are both assessed across time, this initial model does not include time. Therefore, it is incorrect to interpret b_{i1} and G_{10} as "a change in the predictor that is associated with a change in the outcome," a mistake that is too often made in both cross-sectional and multilevel regression analyses. The correct interpretation of these slope terms is that higher levels of the predictor variable are associated with higher levels of the outcome variable, and vice-versa. This is a subtle, yet very important, distinction.

The initial model described above provides a means to examine an association between two variables when they both are collected at multiple time points. Someone who is new to the multilevel regression framework might reasonably ask why not simply use a Pearson's correlation coefficient using a standard software application. The answer is that one of the assumptions underlying standard (i.e., not multilevel) correlation and regression analyses is that observations (i.e., data points) are independent, and with nested data structures, this assumption is violated. In the repeated measures framework, there is some dependency in the data because a data point from one particular participant will be more like other data points for that participant than data points from another participant. This is why multilevel regression analyses are needed. They account for the nested (i.e., hierarchical) nature of the data and do not require the "independence of observations" assumption.

The initial model described above does not include time, so it provides no information regarding how changes in one variable are related to changes in another variable. The next section will incorporate time by describing standard growth curve models building towards a multivariate model that can assess how change in one variable is associated with change in another variable (i.e., correlation of change or trajectories).

STANDARD (UNIVARIATE) GROWTH CURVE MODEL USING MULTILEVEL REGRESSION

King, King, Salgado, and Shalev (2003) provided a detailed account of how to conduct growth curve analyses within a multilevel regression framework to examine posttraumatic adaptation. The standard growth curve model examines the nature of change in one outcome variable. This model is briefly reviewed to provide a foundation for examining multivariate change (i.e., how change in one variable is correlated with change in another variable over time).

The Level 1 regression equation for a standard (univariate) growth curve model is

$$Y_{it} = b_{i0} + b_{i1}\text{time} + e_{it} \tag{5}$$

Again, Y_{it} denotes that the equation is predicting the outcome variable Y, for a particular participant i, at a particular assessment occasion t. Next, b_{i0} denotes the regression intercept representing initial status of the outcome variable (with the first assessment occasion coded 0 in the time variable) for individual i, and b_{i1} denotes the regression coefficient representing change over time in the outcome variable (i.e., slope) for participant i. Finally, e_{it} represents the regression residual term indicating how far a data point deviates from the expected value (or regression line) for participant i at time t. Time can be represented in several ways in the Level 1 equation to model different forms of change (e.g., linear, nonlinear, piecewise, etc.; for descriptions of different ways to represent time, see Biesanz, Deeb-Sossa, Papadakis, Bollen, & Curran, 2004; Singer & Willett, 2003). Using the data for our demonstration (to follow), we examine linear change across five assessment occasions. As will be seen, time is represented as the number of months since the rape or robbery, coded 0, 2, 5, 11, and 17, depending on the assessment occasion (number of months minus one, so that the intercept coefficient represents initial status).

The Level 2 regression equations for a standard (univariate) growth curve model are

$$b_{i0} = G_{00} + U_{i0} \tag{6}$$

$$b_{i1} = G_{10} + U_{i1} \tag{7}$$

The Level 2 coefficients represent the Level 1 coefficients averaged across Level 2 units. Therefore, G_{00} and G_{10} represent averages across all participants in initial status and change over time; U_{i0} and U_{i1} reflect the degree to which the Level 1 coefficients vary across Level 2 participants (i.e., are there significant individual differences in initial status and change over time?). In sum, standard growth curve analyses elucidate how a single dependent variable changes over time and provides estimates of mean initial status and change over time and the degree to which these change parameters vary across participants. For example, military researchers examining postdeployment adaptation might be interested in knowing the average postdeployment PTSD severity level of the sample (G_{00}) upon return from a war zone and how much variability there is in this initial postdeployment PTSD severity level (U_{i0}), as well as the average change over time in PTSD severity (G_{10}) for an extended amount of time postdeployment and how much variability in change over time in PTSD severity is present (U_{i1}). They may also be interested in the degree to which initial status and change over time is correlated, addressing the question of whether or not individuals who initially exhibit more severe PTSD symptoms show larger (or smaller) decreases over time.

MULTIVARIATE GROWTH MODEL

Though typically used to study change in one variable, MacCallum and colleagues (1997) demonstrated that growth-curve modeling with multilevel regression can be extended to the multivariate situation to examine how trajectories of two variables are correlated. In this section, we provide the fundamentals of this procedure and encourage readers interested in more specific/technical details to consult MacCallum et al. (1997). Multivariate growth-curve models involve computing two or more growth curves simultaneously in one model.

The Level 1 regression equation for the multivariate growth curve model is

$$Y_{it} = b_{i1}\text{D\_intr} + b_{i2}\text{T\_intr} + b_{i3}\text{D\_avoid} + b_{i4}\text{T\_avoid} + e_{intrusion} + e_{avoidance} \tag{8}$$

The first difference between the multivariate Level 1 Equation 7 and the univariate Level 1 Equation 4 is that the multivariate equation does not include an overall intercept (b_{i0}). Dummy-coded variables (D_intr and D_avoid) are included in the data set to specify when the outcome variable is intrusion and when it is avoidance.[2] This creates separate intercepts (or initial values) for intrusion and avoidance. Therefore, b_{i1} represents the intercept for intrusion, and b_{i3} represents the intercept for avoidance. Likewise, b_{i2} and b_{i4} represent change over time in intrusion and avoidance, respectively. The second major difference is that the Level 1 residual is split into two terms, $e_{intrusion}$ and $e_{avoidance}$, representing the Level 1 random residuals of intrusion and avoidance, respectively.[3]

The Level 2 regression equations for the multivariate growth curve model are

$$b_{i1} = G_{10} + U_{i1} \tag{9}$$

$$b_{i2} = G_{20} + U_{i2} \tag{10}$$

$$b_{i3} = G_{30} + U_{i3} \tag{11}$$

$$b_{i4} = G_{40} + U_{i4} \tag{12}$$

The Level 2 regression equations represent the aggregation of Level 1 coefficients and the associated Level 2 residuals. Therefore, G_{10}, G_{20}, G_{30}, and G_{40} provide estimates of initial status in intrusion, change over time in intrusion, initial status in avoidance, and change over time in avoidance, respectively, aggregated across participants.

Multilevel regression analyses produce estimates of the variances and covariances of the Level 1 coefficients as well as the standard errors for these estimates (i.e., the tau matrix, the variance/covariance matrix for the random effects; see Raudenbush, Bryk, & Congdon, 2005, for details). The strength and statistical significance of the association in change over time between two variables (i.e., correlation of change, or how much change in one variable is associated with change in the other) can be evaluated by examining the estimate of the covariance between the two Level 1 slope coefficients (b_{i2} and b_{i4}). This will be illustrated in the next section, where we use the procedures above to examine the relationship between intrusion and avoidance symptoms over time with real data.

DEMONSTRATION OF MULTILEVEL REGRESSION ANALYSES TO EXAMINE THE RELATIONSHIP BETWEEN INTRUSION AND AVOIDANCE SYMPTOMS OVER TIME

As noted previously, the data for this demonstration came from 340 individuals who experienced a recent rape or robbery (Resick, 1988). Participants were assessed within one month ($n = 286$) of experiencing the traumatic event and at follow-up assessments occurring 3 ($n = 217$), 6 ($n = 184$), 12 ($n = 105$), and 18 ($n = 119$) months posttrauma. Although participants were assessed 1, 3, 6, 12, and 18 months postrape or postrobbery, the time variable was coded as 0, 2, 5, 11, and 17 so that the intercept term represents intrusion and avoidance levels upon entry into the study (one month following the rape or robbery). One of the advantages of multilevel regression analyses is efficiency in handling unbalanced data. It is not a problem for the number of data points to vary across participants, and data from participants with just one data point are be included in the analyses. To parallel the presentation to this point, the demonstration addresses three questions: (a) what is the bivariate association between symptoms of intrusion and avoidance across all assessment occasions?; (b) how do symptoms of intrusion and avoidance change over time?; and (c) are changes in intrusion associated/correlated with changes in avoidance? Intrusion and avoidance symptoms were assessed by the Impact of Event Scale (IES; Horowitz, Wilner, & Alvarez, 1979), a 15-item self-report measure of distress subsequent to stressful life events. Individuals are asked to rate the frequency of intrusion (seven items) and avoidance (eight items) symptoms during the previous 7 days. Responses are rated on a 4-point Likert scale: 0 = *not at all*, 1 = *rarely*, 3 = *sometimes*, 5 = *often*. The IES has been widely used for 30 years and has demonstrated adequate reliability and validity (Sundin & Horowitz, 2002). Although item values are usually summed to form subscale totals, we analyzed average scores

[2] For detailed descriptions of how to set up a data file to conduct multivariate growth curve analyses, see Bauer, Preacher, & Gil, 2006; MacCallum, Kim, Malarkey, & Kiecolt-Glaser, 1997; or contact the first author.

[3] For a description of how to accomplish this using HLM, see Raudenbush, Bryk, & Congdon, 2005, or contact the first author.

for the intrusion and avoidance subscales so the two variables of interest would be on the same metric. Intrusion and avoidance are separate, distinct constructs. However, because participants rate how frequently they experience each type of symptom, the total scale scores represent the frequency with which one experiences intrusion and avoidance, but please note that care must be taken when comparing the metric of two different scales or subscales. Hereafter, we use the term *intrusion* to refer to the frequency of intrusion symptoms, and *avoidance* to refer to the frequency of avoidance symptoms.

We conducted all analyses with the software program Hierarchical Linear and Non-Linear Modeling (HLM6; Raudenbush et al., 2005) using full maximum likelihood estimation. The HLM program was one of the first packages specifically designed for analyzing nested data. Hence, it is quite efficient. However, many other statistical packages can be used to evaluate multilevel models (e.g., Peugh & Enders, 2005; Rabe-Hesketh & Skrondal, 2005; Singer, 1998).

A helpful first step when conducting multilevel regression analyses is to examine what is referred to as the "unconditional model," or intercept-only model, that is, a model that includes no predictor variables. Consistent with the nomenclature presented earlier, the Level 1 equation for the unconditional model is $Y_{it} = b_{i0} + e_{it}$; the Level 2 equation is $b_{i0} = G_{00} + U_{i0}$. G_{00} provides an estimate of the overall mean of the outcome variable when taking into account the nested structure and unbalanced nature (i.e., varying number of assessment points across participants) of the data. The aggregation of e_{it} provides an estimate of σ^2, or the total Level 1 (within-subjects) variance, and the aggregation of U_{i0} provides an estimate of the overall Level 2 (between-subjects) variance.

The top section (Unconditional model) of Table 1 depicts the results of the unconditional model with intrusion and avoidance as outcomes in separate analyses. The regression intercept of the unconditional model indicated that when averaged across assessment occasions and individuals, participants tended to endorse experiencing avoidance ($G_{00} = 1.38$) more frequently than intrusion ($G_{00} = 1.14$). Nonoverlapping 95% confidence intervals (CIs) indicate a statistically significance difference. The distribution of variance was also slightly different for the two outcome variables, with total variance being slightly more evenly distributed across Level 1 (51%) and Level 2 (49%) for avoidance compared to intrusion (45% and 55% for Level 1 and Level 2, respectively). The information provided by the unconditional model provides a context to help evaluate the primary analyses including initial estimates of variance, from which estimates of variance accounted for by including predictors can be derived.

The second section (Analysis 1: Bivariate association) of Table 1 provides the results of the analyses examining the bivariate association between intrusion and avoidance averaged across all of the assessment occasions. The estimates of G_{10} were .71 and .68 for the models with intrusion and avoidance as the outcomes, respectively. Both of these estimates were associated with high t statistics, and were both statistically significant at $p < .001$, suggesting a significant positive association between intrusion and avoidance. Comparing estimates of σ^2 (within-subjects variance) for the current model with estimates of σ^2 from the unconditional model allows for the computation of a percentage change in σ^2 ($\Delta\sigma^2$). This is analogous to R^2 in ordinary least squares regression and indicates how much Level 1 (within-subjects) variance is accounted for by the predictor(s). Estimates of $\Delta\sigma^2$ indicate that avoidance accounted for 49% ($r = .70$) of the Level 1 variance in intrusion, whereas intrusion accounted for 44% ($r = .63$) of the variance in avoidance, both suggesting a strong association between intrusion and avoidance. Given that G_{10} for both models provides estimates for the same intrusion–avoidance association, it should be noted that the estimates are not identical when switching the position of the predictor and outcome variables. The slight disparity that arises is due to the small difference in the dispersion between intrusion and avoidance, as evident in the discrepancy in the variance components of the unconditional model. Regardless, both estimates suggest a relatively strong positive association between intrusion and avoidance.

The third (Analysis 2: Standard growth curve) and fourth (Analysis 3: Multivariate growth curve) sections of Table 1 summarize the results of the univariate and multivariate growth curve analyses. The estimates of the fixed effects (i.e., average initial status and change over time) are almost identical across the univariate and multivariate models, supporting the viability of the multivariate approach. Therefore, we will interpret them simultaneously. The estimates of G_{00} indicate that on average, participants entered the study with an intrusion score of 1.42 (on the 0–5 scale) and an avoidance score of 1.64 (on the same scale). The significance tests associated with these coefficients indicate that these estimates are both significantly greater than 0. Significance tests associated with G_{10} (slope) indicate that there was a significant mean-level decrease in both intrusion and avoidance over time. Because intrusion and avoidance scores were on the same metric, the 95% CIs can be examined for overlap to determine whether or not mean levels of initial status and change over time differed across the two outcome variables. As shown in Table 1, there was overlap in the CIs for initial status and slope (for both the univariate and multivariate models), suggesting no mean-level differences between intrusion and avoidance. The estimates of Level 1 variance accounted for by time vary slightly between the univariate and multivariate growth curves. The univariate models produced estimates of $\Delta\sigma^2$ of .15 and .18 for intrusion and avoidance, respectively, suggesting that time accounts for 15% and 18% of the Level 1 variance for these two outcomes. The multivariate model produced estimates of $\Delta\sigma^2$ of .24 for both intrusion and avoidance for these same coefficients. Our recommendation is to interpret the multivariate estimates, given that the multivariate model includes more information in the computation of the estimates and accounts for differences in Level 1 variance in intrusion and avoidance symptoms. Thus, the growth curve models suggest

Table 1. Summary of the Multilevel Regression Analyses

	Outcome: Intrusion			Outcome: Avoidance		
Unconditional model	Value	t	95% CI	Value	t	95% CI
Fixed effects						
Intercept (G_{00})	1.14*	18.72	1.01-1.24	1.38*	21.62	1.26-1.51
Variance component	Total variance = 1.75			Total variance = 1.86		
	Level 2 variance = .79 (45%); 95% CI = .78-.81			Level 2 variance = .96 (51%); 95% CI = .93-.98		
	$\sigma^2 = .96$ (55%)			$\sigma^2 = .91$ (49%)		
Analysis 1: Bivariate association						
Fixed effects						
Intercept (G_{00})[a]	1.11*	27.99	1.03-1.09	1.38*	31.35	1.29-1.46
Predictor (G_{10})	0.71*	25.19	0.66-.77	0.68*	23.91	0.63-.79
Variance component[b]	$\sigma^2 = .50$, $\Delta\sigma^2 = .49$			$\sigma^2 = .53$, $\Delta\sigma^2 = .44$		
	VAR (G_{00}) = .25, $\Delta DEV(2) = 164.47$, $p < .001$			VAR (G_{00}) = .38, $\Delta DEV(2) = 121.11$, $p < .001$		
	VAR (G_{10}) = .09, $\Delta DEV(2) = 137.23$, $p < .001$			VAR (G_{10}) = .03, $\Delta DEV(2) = 9.25$, $p < .01$		
Analysis 2: Standard growth curve						
Fixed effects						
Intercept (G_{00})	1.42*	20.34	1.28-1.55	1.64*	22.69	1.51-1.79
Time (G_{10})	−0.06*	−10.55	−0.07-−.05	−0.06*	−7.67	−0.07-−.05
Variance component[b]	$\sigma^2 = .81$, $\Delta\sigma^2 = .15$			$\sigma^2 = .75$, $\Delta\sigma^2 = .18$		
	VAR (G_{00}) = .99, $\Delta DEV(2) = 231.07$, $p < .001$			VAR (G_{00}) = 1.14, $\Delta DEV(2) = 252.10$, $p < .001$		
	VAR (G_{10}) = .001, $\Delta DEV(2) = 10.39$, $p < .001$			VAR (G_{10}) = .002, $\Delta DEV(2) = 10.18$, $p < .01$		
Analysis 3: Multivariate growth curve						
Fixed effects						
Intercept	1.43*	20.46	1.29-1.56	1.66*	22.84	1.51-1.80
Time	−0.07*	−10.78	−0.08-−.05	−0.06*	−9.87	−0.08-−.05
Variance component[b]	$\sigma^2 = .72$, $\Delta\sigma^2 = .24$[c]			$\sigma^2 = .67$, $\Delta\sigma^2 = .24$[c]		
	VAR (G_{10}) = 1.07, $\Delta DEV(4) = 371.69$, $p < .001$			VAR (G_{30}) = 1.21, $\Delta DEV(4) = 400.08$, $p < .001$		
	VAR (G_{20}) = .003, $\Delta DEV(4) = 51.73$, $p < .001$			VAR (G_{40}) = .004, $\Delta DEV(4) = 56.78$, $p < .001$		

Note. Value = The unstandardized regression coefficient, t = t statistic, CI = confidence interval, VAR = variance, DEV = deviance statistic.
[a]The predictor variables were grand centered (i.e., average score across all assessment occasions and all participants subtracted from each individual score). Therefore, the intercept term in Analysis 1 can be interpreted as the average score of the outcome when the score of the predictor as at the overall mean).[b] Though hierarchical linear modeling (HLM) provides significance tests of the variance components, many (e.g., Bliese & Polyhart, 2002; Singer, 1998) have argued that these tests are statistically questionable and suggest a model-contrasting approach to evaluate the significance of variance in the Level 1 coefficients across Level 2 units. This entails conducting the analyses twice, first with the coefficient fixed to be constant across Level 2 units and then with the coefficient free to vary across Level 2 units. The results of these two analyses are compared using a log-likelihood based indicator of model fit. A significantly improved model fit when allowing the Level 1 coefficients to vary across Level 2 units indicates significant variation in the Level 1 coefficient. In HLM, the deviance statistic (*DEV*) is a log-likelihood based indicator of model fit, and the difference in the deviance statistic (ΔDEV) has an approximate chi-square distribution with the degrees of freedom equal to the difference in the number of parameters estimated between the two competing models (Raudenbush & Bryk, 2002). This model-contrasting approach was used to test whether or not there was statistically significant variance in the Level 1 coefficients (i.e., initial status and slope) across Level 2 units (i.e., individuals).[c] For the multivariate change model, $\Delta\sigma^2$ is calculated by comparing the estimates of σ^2 from a baseline model with only the intercept terms included for each variable to the estimates of σ^2 from full multivariate change model.
$^*p < .001$.

Table 2. Estimates of Random Effects for Multivariate Growth Curve Model

		Variances, covariances, and intercorrelations of random intercepts and slopes			
		1	2	3	4
1	Intrusion intercept u_{i1}	1.21 (.13) [9.12]	1.04 (.10) [9.55]	−.04 (.01) [−3.69]	−.04 (.01) [−4.33]
2	Avoidance intercept u_{i2}	.92	1.07 −0.11 [9.81]	−.03 (.01) [−2.62]	−.04 (.11) [−.33]
3	Intrusion slope u_{i3}	−.54	−0.392	.004 (.001) [3.80]	$\boxed{.003 \; (.001) \; [4.38]}$
4	Avoidance slope u_{i4}	−.63	−.59	$\boxed{\textbf{.95}}$	.003 (.001) [3.52]
Residual variances:					
Residual variance of intrusion			Var[$e_{it(intrusion)}$]		0.729
Residual variance of avoidance			Var[$e_{it(avoidance)}$]		0.673

Note. The numbers in the upper right triangle and the diagonal are covariances (top) and their standard errors (middle enclosed in parentheses) and critical (z) ratios [bottom enclosed in brackets, calculated by dividing the estimate of the covariance by the standard error]. 1.96 is the critical value for $\alpha = .05$, 2.58 for $\alpha = .01$. The lower triangle contains the correlations. Boxes enclose the estimates depicting the association between change over time in intrusion and change over time in avoidance.

a similar, moderate decrease in intrusion and avoidance symptoms across the five assessment occasions. In other words, over the 17 months of the study (i.e., 1–18 months), these rape and robbery victims demonstrate an expected decrease of .07 units per month for intrusion and .06 units per month for avoidance.

These results revealed similar mean levels of initial status and change over time for intrusion and avoidance. However, this does not necessarily indicate that changes in intrusion are associated or correlated with changes in avoidance. To illustrate, let us consider a hypothetical example of a situation in which similar mean level change would not correspond to correlated change over time in intrusion and avoidance. Imagine that half of the participants exhibited large decreases in intrusion, but no change over time in avoidance, whereas the other half exhibited the opposite pattern, no change in intrusion and large decreases in avoidance. In this situation, if you averaged across all participants, you could find similar mean levels of moderate change in intrusion and avoidance. At the same time, because decreases in intrusion do not correspond to decreases in avoidance, changes in intrusion and avoidance are not correlated with each other. Therefore, whether or not two variables exhibit similar mean levels of change over time is independent of whether or not change in the two variables is correlated.

The covariance–variance matrix of the random effects from the multivariate model includes an estimate of the association between change over time in intrusion and change over time in avoidance. This matrix is presented in Table 2, with coefficients for the primary associations of interest enclosed in boxes. A strong association emerged between slopes (i.e., change over time) for intrusion and avoidance with an estimated correlation of .95 ($r^2 = .90$). Statistical significance can be evaluated by examining the z ratio formed by dividing the estimate of the covariance for this association by the estimate of the standard error of the covariance. This ratio value was 4.38, well over the critical value of 1.96 for a significant effect with $\alpha = .05$. This suggests that changes in the frequency of intrusion symptoms are highly correlated with changes in the frequency of avoidance symptoms. In other words, rape and robbery victims who report significant decreases in the frequency of intrusion symptoms over time tend to report similar decreases in the frequency of avoidance, those who report no change over time in the frequency of intrusion symptoms tend to report no change in the frequency of avoidance symptoms, and those who report increases over time in the frequency of intrusion symptoms tend to report similar increases in avoidance.

FINAL COMMENTS

One way to extend the models described above is to include Level 2 predictor variables. The first model (examining the bivariate relationship across all time points, but not examining change over time) is extremely flexible in terms of the inclusion of Level 2 predictors. Continuous or categorical Level 2 predictors can be included to examine factors that may account for the Level 1 association between variables. For example, negative affectivity/neuroticism has been identified as a generalized biological vulnerability underlying all anxiety and mood disorders, including PTSD (Barlow, 2002). Therefore, the large bivariate association between intrusion and avoidance may be accounted for by negative affectivity/neuroticism. To test this hypothesis, a variable representing negative affectivity/neuroticism could be added to the two Level 2 equations (Equations 3 and 4), and the impact of the inclusion of this variable on the Level 1 intrusion–avoidance bivariate association could be assessed. If the fixed effect is substantially diminished, this would suggest that the intrusion–avoidance association is at least partially accounted for by negative affectivity/neuroticism.

Level 2 predictors can also be included and interpreted as moderators of the Level 1 bivariate association. Drawing upon an example outside of the intrusion–avoidance context, one might hypothesize that the relationship between posttraumatic wellbeing and social support, measured at several different time points after the traumatic event, varies as a function of gender, such that social support is more beneficial for females, based on research suggesting gender differences in stress-response systems (e.g., Taylor et al., 2000). A dummy-coded gender variable could be added to the Level 2 equations to evaluate whether the Level 1 association between wellbeing and social support varies as a function of gender. In a similar manner, Level 2 predictors can be added to the Level 2 equations of univariate and multivariate growth curve models to examine whether or not initial status and change over time varies as a function of a Level 2 variable.

Multivariate change can be examined using multilevel regression analyses or structural equation modeling (SEM)/latent growth curve procedures (an alternative framework for conducting growth curve analyses, see Chou, Bentler, & Pentz, 1998). MacCallum et al. (1997) provided a comparison of these two approaches. They emphasized that both approaches are powerful and many analyses can be conducted using either approach with comparable results. They suggested that one advantage of the multilevel approach is that it is more flexible in the variety of ways that nonlinear change can be incorporated. Plewis (2005) demonstrated how multilevel multivariate growth curve models can include parameters that model nonlinear/curvilinear change. On the other hand, they note that SEM/latent growth curve models offer more flexibility when examining correlates, predictors, and consequences of change. These approaches offer different advantages and disadvantages, and the data structure available and research question at hand should be used to determine which approach is most suitable.

We conclude by highlighting one of the primary advantages of the multilevel regression approach: It is very flexible, both in the models that can be evaluated (demonstrated above) and in the types of data structures that it can accommodate. As noted earlier, the number and timing of assessment points do not have to be constant across participants. Therefore, one participant can have five data points assessed at 1, 2, 3, 4, and 5 months postevent, whereas another participant can have two data points assessed at 3 and 7 months postevent. In this sense, multilevel regression approaches are much more accommodating than SEM/latent growth curve approaches. We hope that this discussion of multilevel regression will encourage further development and use of innovative methodologies to advance longitudinal trauma research.

REFERENCES

Barlow, D. H. (2002). Anxiety and its disorders: The nature and treatment of anxiety and panic (2nd ed.). New York: Guilford Press.

Bauer, D., Preacher, K., & Gil, K. (2006). Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: New procedures and recommendations. Psychological Methods, 11, 142–163.

Biesanz, J. C., Deeb-Sossa, N., Papadakis, A. A., Bollen, K. A., & Curran, P. J. (2004). The role of coding time in estimating and interpreting growth curve models. Psychological Methods, 9, 30–52.

Bliese, P. D., & Polyhart, R. E. (2002). Growth modeling using random coefficient models: Model building, testing, and illustrations. Organizational Research Methods, 5, 362–387.

Bonanno, G. (2004). Loss, trauma, and human resilience: Have we underestimated the human capacity to thrive after aversive events? American Psychologist, 59, 20–28.

Chou, C. P., Bentler, P. M., & Pentz, M. A. (1998). Comparison of two statistical approaches to study growth curves: The multilevel model and the latent curve analysis. Structural Equation Modeling, 5, 247–266.

Coffey, S. F., Schumacher, J. A., Brady, K. T., & Cotton, B. D. (2007). Changes in PTSD symptomatology during acute and protracted alcohol and cocaine abstinence. Drug and Alcohol Dependence, 87, 241–248.

Creamer, M., Burgess, P., & Pattison, P. (1992). Reaction to trauma: A cognitive processing model. Journal of Abnormal Psychology, 101, 452–459.

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. Psychological Methods, 12, 121–138.

Horowitz, M. J., Wilnser, N., & Alvarez, W. (1979). The Impact of Event Scale: A measure of subjective stress. Psychosomatic Medicine, 41, 209–218.

King, L. A., King, D. W., Salgado, D. M., & Shalev, A. Y. (2003). Contemporary longitudinal methods for the study of trauma and posttraumatic stress disorder. CNS Spectrums, 8, 686–692.

Litz, B. T. (2007). Research on the impact of military trauma: Current status and future directions. Military Psychology, 19, 217–238.

MacCallum, R. C., Kim, C., Malarkey, W. B., & Kiecolt-Glaser, J. K. (1997). Studying multivariate change using multilevel models and latent curve models. Multivariate Behavioral Research, 32, 215–253.

Peugh, J. L., & Enders, C. K. (2005). Using the SPSS mixed procedure to fit cross-sectional and longitudinal multilevel models. Educational and Psychological Measurement, 65, 714–741.

Plewis, I. (2005). Modeling behaviour with multivariate multilevel growth curves. Methodology: European Journal of Research Methods for the Behavioral and Social Sciences, 1, 71–80.

Rabe-Hesketh, S., & Skrondal, A. (2005). Multilevel and longitudinal modeling using Stata. College Station, TX: StataCorp LP.

Raudenbush, S. W., & Bryk, A. S. (2002). Hierarchical linear models: Applications and data analysis methods (2nd ed.). Thousand Oaks, CA: Sage.

Raudenbush, S., Bryk, A., & Congdon, R. (2005). HLM 6: Hierarchical linear and nonlinear modeling [Computer software]. Lincolnwood, IL: Scientific Software International.

Resick, P. A. (1988). Reactions of female and male victims of rape or robbery (Final report, grant #85-IJ-CX-0042). Washington, DC: National Institute of Justice.

Schnurr, P. P., Hayes, A. F., Lunney, C. A., McFall, M., & Uddo, M. (2006). Longitudinal analysis of the relationship between symptoms and quality of life in veterans treated for posttraumatic stress disorder. Journal of Consulting and Clinical Psychology, 74, 707–713.

Singer, J. D. (1998). Using SAS PROC MIXED to fit multilevel models, hierarchical models, and individual growth models. Journal of Educational and Behavioral Statistics, 24, 323–355.

Singer, J. D., & Willett, J. B. (2003). Applied longitudinal data analysis. New York: Oxford University Press.

Sundin, E. C., & Horowitz, M. J. (2002). Impact of Event Scale: Psychometric properties. British Journal of Psychiatry, 180, 205–209.

Taylor, S., Klein, L., Lewis, B., Gruenewald, T., Gurung, R., & Updegraff, J. (2000). Biobehavioral responses to stress in females: Tend-and-befriend, not fight-or-flight. Psychological Review, 107, 411–429

Vogt, D., King, D., & King, L. (2007). Risk pathways for PTSD: Making sense of the literature. In M. J. Friedman, T. M. Keane, & P. A. Resick (Eds.), Handbook of PTSD: Science and practice (pp. 99–115). New York: Guilford Press.

Technical Appendixes for:

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Appendix A

More Detailed Description of "Centering"

(Pages 623 and 624)

The term "centering" refers to subtracting a value from each score of a predictor variable. "Mean centering" is the most common type of centering utilized and consists of subtracting the mean value of a variable from each score in a distribution. There are two primary reasons for mean centering: (a) when mean-centered variables are entered into a regression model, the intercept coefficient can be interpreted as the value of the outcome at the mean of the predictor variable (instead of the value of the outcome when the predictor variable is zero, as is the case for non-centered predictors), and (b) when examining interactions, mean centering before creating product terms reduces multicolinearity due to large bivariate associations between the product terms and the predictor variables. Centering in a multilevel regression framework can be quite complex because Level-1 variables can be centered based on each Level-2 unit's (participant's) mean ("group centering") or the mean of all scores across all participants ("grand centering"). Enders and Tofighi (2007) described the implications of these different types of centering. For the current paper, grand centering was exclusively used. In other words, centering was based on the grand mean computed using all scores across all participants.

Appendix B

Setting Up a Data File to Conduct Multivariate Change Analyses

(Footnote 2: Page 625)

The first step in conducting a multivariate change analyses is to set up an appropriate data file (see Figure 1). Let us briefly return to the univariate model, where the data must be stacked so that each row of data represents one assessment occasion; therefore, each participant has multiple rows of data, one for each assessment point. The top part of Figure 1 is structured to conduct two separate univariate growth-curve models, one for intrusion and one for avoidance, where each participant has five rows of data. There are four columns containing an identity variable, an intrusion score, an avoidance score, and a time variable (month of assessment). The bottom half of Figure 1 shows how the data need to be restructured to conduct a multivariate model. The columns for the outcome variables, intrusion and avoidance, have been combined into one column, labeled outcome, with the intrusion values in the top five rows and the avoidance values in the bottom five rows of the column. Therefore, each participant now has 10 rows of data (first five rows for intrusion scores, second five rows for avoidance scores). The outcome variable is followed by two dummy-coded variables. D_intr marks the rows for which the outcome variable contains intrusion scores. A value of 1 indicates that the outcome score is intrusion, while a value of 0 specifies that it is an avoidance score. D_avoid marks the rows for which the outcome variable contains avoidance scores, with the opposite coding scheme of D_intr. These two dummy-coded variables are followed by three time variables: Time, T_intr, and T_avoid. Time demarks the assessment occasion (in number of months), and T_intr and T_avoid are computed by multiplying Time by the D_intr and D_avoid variables. For T_intr, the column contains the values of the time variable (0, 2, 5, 11, 17) for rows with the outcome variable containing intrusion scores and zeros for rows with the outcome variable containing avoidance scores, and vice-versa for the T_avoid variable.

Appendix C

More Information On Specifying Separate Level-1 Residual Terms for Each

Outcome

(Footnote 3: Page 625)

To accomplish this using HLM, a heterogeneous σ^2 can be specified in the "Estimation Settings" options under the "Other Settings" pull-down menu with one of the dummy-coded outcome marker variables [D_intr or D_avoid] as a predictor of Level-1

Univariate Data Structure

ID	Intrusion	Avoidance	Time
1	2.57	1.88	0
1	1.71	1.75	2
1	2.43	2.25	5
1	5.00	2.38	11
1	1.57	2.13	17
2	2.14	3.38	0
2	2.43	3.50	2
2	2.43	1.38	5
2	0.43	0.38	11
2	.	.	17

Multivariate Data Structure

ID	Outcome	D_intr	D_avoid	Time	T_Intr	T_Avoid
1	2.57	1	0	0	0	0
1	1.71	1	0	1	2	0
1	2.43	1	0	2	5	0
1	5.00	1	0	3	11	0
1	1.57	1	0	4	17	0
1	1.88	0	1	0	0	0
1	1.75	0	1	1	2	2
1	2.25	0	1	2	5	5
1	2.38	0	1	3	11	11
1	2.13	0	1	4	17	17

Figure 1. Illustration of data structures. Adapted from Figure 3 of Bauer, Preacher, and Gil (2006).

variance; see Raudenbush, Bryk, & Congdon, 2005, for further details.

Appendix D

More Information On the Variance/Covariance Matrix for the Random Effects

(Page 625)

In HLM, matrices labeled tau containing the variances and covariances for the random effects are printed in the output. For standard models using full maximum likelihood estimates, three matrixes for tau are printed in the output: tau (estimates of variance and covariance), the standard error of tau, and tau as correlations. When specifying a heterogeneous σ^2, only tau and tau as correlations are included in the output. However, the standard errors for tau can be obtained by requesting the variance-covariance matrices be saved into another file. This request can be specified in the "Output Settings" menu located under the "Other Options" pull-down menu. The file that is produced is labeled "tauvc.dat", and the diagonal of the bottom matrix contains the standard errors of tau (see Raudenbush, Bryk, & Congdon, 2005, for further details).